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Affect Detection for Human-Horse Interaction

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***Abstract*—In this work, we aim to study the potential use of affect recognition techniques for examining the interaction between humans and horses using qualitative and quantitative methods. To this end, we propose a multi-modal portable system for physiological signal acquisition such as the electrocardiogram (ECG), electromyogram (EMG), and electroencephalogram (EEG). The proposed system is used to acquire signals while users are interacting with horses. The captured signals will then be used in order to quantitatively evaluate human and equine interaction by mapping the signals to the emotional state of the subjects using machine learning techniques. In this preliminary study, ECG based features were utilised in order to create a supervised classification model that can identify emotions elicited during human-horse interaction. Experimental results provide evidence about the efficiency of the proposed approach in distinguishing between negative and positive emotions, reaching a classification accuracy of 74.21%.**

***Index Terms*—Emotion recognition, physiological signals, human/horse interaction, EEG, ECG, EMG.**

I. Introduction

The relationship between humans and horses has been well documented throughout the history and has been studied extensively. Many recent studies focus on using the interaction with horses for treating mental health issues, such as anxiety and post-traumatic stress symptoms [1], and learning difficulties [2]. Other studies have been undertaken measuring brain activity (electroencephalography - EEG) for specific purposes, such as treating children with autism [3], while the heart rate measurement has also been employed to estimate the interaction between human and horses [4], [5]. Emotional cues may be seen in humans through different channels, such as voice, posture, and expression pheromones [6]. The use of analytical methods for measuring the effect of the interaction with horses on humans has the potential to offer a powerful insight on the benefits of such interaction in psychotherapy intervention.

Affect recognition is the task of detecting the emotional state of humans under various conditions. The development of efficient and robust algorithms for automated emotion (affect) recognition is a major challenge and may have great implications on the way users interact with computers, as well as on fields like medicine, education, multimedia, etc. Human emotion can be recognised through various means such as facial images, gesture, neuro-imaging methods, and physiological signals [1]. Various theories and methods for emotion recognition have been proposed and developed, but their limited performance renders affect recognition as an open research problem. Physiological signals have been widely exploited for the task of affect recognition [7]. Amongst them, the Electroencephalogram (EEG), the Electrocardiogram (ECG), and the Electromyogram (EMG) are some of the most widely used. The EEG is the recording of the electrical activity on the scalp, the ECG is the recording of electrical activity created in the heart, and the EMG is the recording of electrical activity produced by muscle contraction.

In this work, we aim to exploit physiological signals in order to study the potential use of affect recognition techniques for examining the interaction between human and horses. To this end, we propose a multi-modal system and an experimental procedure for acquiring physiological signals in order to detect the human emotion toward different horses. The proposed system was used in order to acquire EEG, ECG, and EMG recordings from people that were interacting with two different horses. Feedback about the interaction was also acquired in the form of video-recorded interviews which were used in order to conduct a qualitative analysis of the emotional responses elicited to the people by their interaction with each of the horses. In this preliminary study, features extracted from the ECG recordings were used in supervised classification experiments for the task of mapping people's descriptions of their own emotions onto their ECG signals. Experimental results provided evidence about the efficiency of the proposed approach, achieving a classification accuracy of 74.21%.

The rest of this paper is organised in four sections. Section II provides an overview of the current state-of-the-art in the examined field. The proposed methodology is described in Section III, while results are presented and discussed in Section IV. Finally, conclusions are drawn in Section V.

II. Background

Emotion is defined as a psycho-physiological process which is elicited by cognisant and/or incognisant grasp of such an article or situation [8]. Personality, mood, behaviour, and inspiration correlate with emotion. Emotions are evident in personal or social communication and can be presented by expressive words orally, or expressed by non-verbal signs such as facial expressions and gestures. Human emotion varies depending on the stimuli that a person is exposed to. Wioleta [9] argues that emotion is affected by many aspects of everyday life: peoples emotions can change according to environment, mood, time, and memory, the same stimuli may create different emotions for different people, and the same emotion may be seen at different intensities, and conclude that it is impossible to have a specific emotion or even any emotion you want. Detecting and measuring the felt emotions is an arduous task.

Physiological signal is one of the tools that can describe human emotions [10]. Physiological signals are attracting research attention as a way of mapping peoples emotions. For example, studies have shown that there is a relation between physiological signals and the arousal and valence dimensions of a felt emotion, and multiple studies have examined the use of multi-modal systems for capturing physiological signals and mapping them to an emotional state, e.g. [7], [8].

While various studies have been conducted for examining equine assisted therapy, e.g. [11], [12], relatively few academic studies have focused on understanding the complex emotional response that horses seem to elicit to human riders, handlers and even artists. Emotional response to human/horse interaction dates back at least to the earliest existing writing about horsemanship. Xenophon [13] advised on how to train the horse with gentleness so as to develop and enjoy his natural beauty and power. Duarte [14] wrote about the way in which horse riding forces the rider to master one's fear, anger, frustration, and the ego and to develop judgement, tranquillity, and wisdom. Similarly, De Pluvinel [15] advised his student (the Dauphin of France) that the study of horsemanship taught kingly virtues and wisdom in life, an opinion echoed by Podhajsky [16], dressage Olympic medallist and one time Director of the Spanish Riding School more than three hundred years later [17]. De Kunffy [18] discusses the ultimate aim of becoming one with the horse and the overpowering sensation of emotion to be experienced with this attainment.

A qualitative study into the personal reasons for dedicating a life to classical dressage describes the rider/trainers search for "*brilliance*", an emotion and feeling that once experienced is addictive [19]. In addition to such recorded descriptions of the ability of the horse to evoke powerful emotions in their riders/handlers, proponents of *Natural Horsemanship* attempt to enhance the emotional satisfaction riders/handlers experience in their relationship with the horse. The particular emotional relationship that women and girls experience with horses has also been recorded, e.g. [20], [21]. As a counter to what has sometimes been described as more anecdotal evidence, advocates of evidenced-based research in the form of *Equitation Science* have posited ideas of learning theory to help riders/handlers improve both horse welfare and enhance the quality of the human/horse relationship, e.g. [22].

Given the emotional richness of the human/horse relationship it is perhaps not surprising that therapists value the contributions that horses can make to the psychotherapy process. Thus, horses have been considered as one of human beings best friends. One of the goals of the research about horse-human relationship is to try to enhance the development and maintenance of a solid positive relationship that can be elicited in a short action and seen in a short time [23].

Recently, researchers have been trying to explore the interaction between human and horses using physiological signals. Lanata et al.'s [24] study focuses on human-horses interaction by using ECG signals. The signals were captured in three phases, before interaction, visual-olfactory interaction, and grooming. In this study, ECG-based features were used with a Support Vector Machine (SVM) classifier for the task of identifying the interaction activity between the human and the horse, reaching a classification accuracy of 90.95%. Another study by the same researchers on the same topic, using the same activities, but with a different classifier (Nearest Mean classifier), reached an accuracy of 70.87% [25].

III. Methodology

A. Participants

Two healthy horses, chosen by the handler, were involved in this study (*Max*, Appaloosa stallion, 19 years old, and *Braga*, Lusitano stallion, 7 years old), and eleven participants with different experiences with horses, enrolled in this experiment (see Fig. 2). Their ages were between 16 and 64 years old ($\mu = 36.45$, $\sigma = 16.84$). It must be noted that for conducting this study and for publishing the results and acquired data, ethical approval was acquired from University of the West of Scotland, University Ethics Committee.

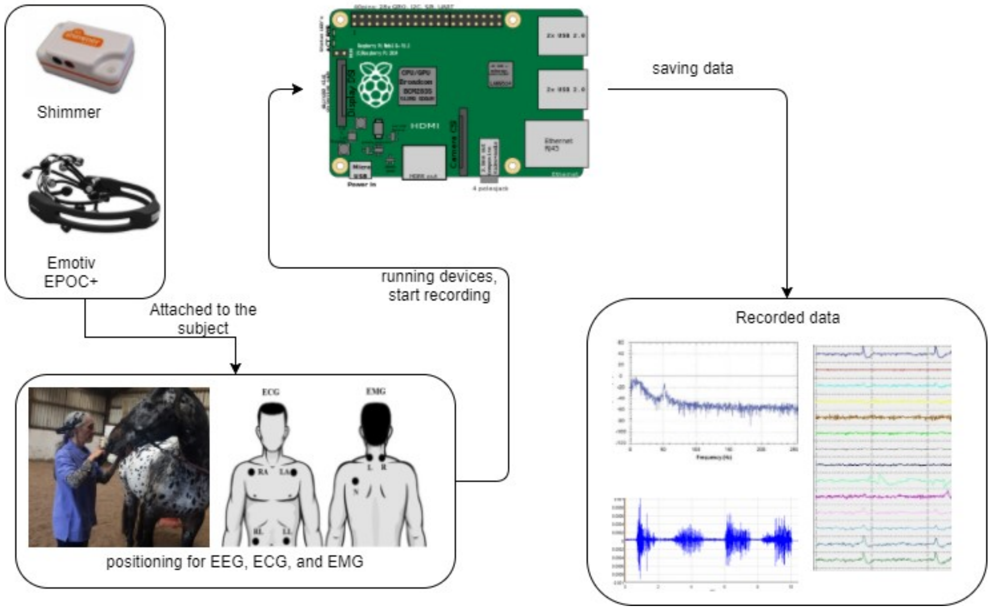

Fig. 1: The signal acquisition system

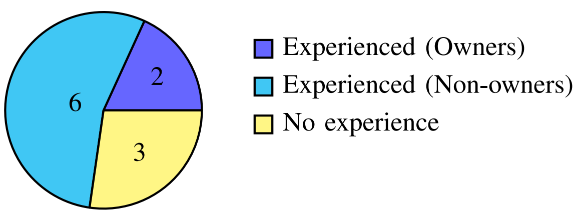

Fig. 2: Division of participants based on their previous experience with horses. The owners of the horses used in this study are referred as “Owners”.

B. Procedure

Before starting the experiment, a consent form was distributed, and instructions were given to the subjects individually. The duration of the experiment was approximately ten minutes for each horse, divided to three phases relating to performed activities (looking, grooming, and leading the horses). Phase 1 (looking) lasted four minutes. Its purpose was to let the subject and horse become comfortable with each other. The subject was asked to sit down while the horse was free to move for four minutes in a small indoor sand arena. This process allowed the horse to explore the changes to their familiar environment caused by the experiment [4]. Next, the participant was asked to start the second activity which was grooming (touching) the horse. Touching horses has been shown to result to a decrease in human and horse heart rates when they are both comfortable [5]. The subject spent two minutes grooming the horse. Finally, for Phase 3, the subject was asked to lead the horse around a predetermined path. The duration of this activity depended on the subject’s movement and the subject’s confidence and ability in controlling the horse’s movement. The above procedures were repeated two times for each subject, one for each of the two horses used in the study. Between each iteration of the experiment, there was a ten minutes break in order to allow the handler to bring the next horse to the arena and prepare the subject for the next experiment. The whole experiment, as well as an interview with each subject about their interaction with the horses was video-recorded for reference and validation purposes.

C. Data collection

In order to examine the relation between physiological signals and human and horse interaction, EEG, ECG, and EMG data were captured for each subject during the three phases of the experiment. EEG was recorded at a sampling rate of 128 Hz using the Emotiv EPOC+ wireless EEG headset [26] that has 16 gold-plated contact sensors that are fixed to flexible plastic arms of the Emotiv EPOC wireless headset and are placed against the head in locations aligned with the following locations according to the International 10-20 system: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4, M1 and M2. ECG and EMG were recorded at a sampling rate of 256 Hz using two wireless Shimmer sensors [27], and using four standard electrodes placed on both lower ribs and clavicle for

TABLE I: Keywords associated with positive and negative emotion

Keyword	Emotion
Comfortable, Calm, Impressed, Relaxed, Happy Nice, Great, Enjoyed, Proud	Positive
Afraid, Scared, Wary, Uneasy, Aware	Negative

TABLE II: Classification performance

Classifier	Accuracy	F1-score
1-NN	0.6528	0.6449
DT	0.7163	0.6943
LDA	0.6667	0.6518
SVM (Linear)	0.7361	0.7170
SVM (RBF)	**0.7421**	**0.7218**

ECG, and three standard electrodes placed on the upper trapezius muscles for EMG [28].

All devices were connected to a Raspberry Pi portable mini-computer that was powered by a standard off-the-shelf USB power bank, and the acquired signals were recorded and stored on the Raspberry Pi's micro SD memory card. The use of the aforementioned computing device as the control and capturing module of the proposed system ensured that the necessary portability for conducting equine related studies on outdoors environments was achieved. An outline of the proposed system and setup is shown on Fig. 1. When all the activities were completed, a video-recorded interview was conducted with each participant in which they were asked to reflect upon their experience with each of the two horses.

D. Data pre-processing and preparation

Using the timestamps from the video recordings of each experiment, the acquired signals were divided into segments referring to each phase of the experiment. Following this procedure, each of the EEG, ECG, and EMG recordings was divided into six segments, one referring to each phase and horse. Furthermore, each segment was further divided into 10 sec segments with 25% overlap. Then, each sample was labelled as referring to positive or negative emotion by using the participants' interviews to detect keywords about how they felt during each phase of the experiment. Russel's [29] circumplex model of affect was used in order to associate the expressed felt emotion as negative of positive, depending on whether it was associated with negative or positive valence respectively. For example, if a participant stated that he felt fear during a phase of the experiment, then the signal segments referring to this phase were labelled as referring to a negative emotion. Table I shows all the detected keywords associated with negative and positive emotion.

This labelling process led to a highly unbalanced dataset, with 77.08% of the samples referring to positive emotion and only 22.92% of samples referring to negative emotion. To address this issue and balance the class ratios within the dataset, samples referring to positive emotion were randomly discarded while the ratio of samples referring to each phase of the experiment were kept constant. The final balanced dataset contained 504 samples, with 43.06% of them belonging to the negative class and 56.94% belonging to the positive class due to the constraint of maintaining the ratio of samples referring to each phase of the experiment.

E. Feature extraction

In this preliminary study, we then attempted to use statistical features extracted from the ECG recordings in order to train a machine learning model for detecting the affective state of the participants during their interaction with the horses. Features extracted from ECG signals have been shown to correlate with changes in the affective state of a person [30], [31], [32]. The most commonly used ECG features are heart rate (HR) and heart rate variability (HRV) specific parameters in the time and frequency domain respectively. Rainville et al. [33] showed that heart rate variability may decrease with fear, sadness and happiness, while pleasantness may lead to an increase in the peak heart rate [34].

To this end, HR and HRV features derived from the recorded signals were computed for use in the proposed machine learning approach. QRS complexes and R-peaks within the ECG signals were detected using the Pan-Tompkins QRS detection algorithm [35] and the Augsburg Biosignal Toolbox (AuBT) [36] was used in order to compute 84 statistical features from each part of the PQRST complexes. The extracted features were the maxima, minima, mean, median, standard deviation and range from the raw signal and the derivative of PQ, QS and ST complexes, the number of intervals with latency $> 50\ ms$ from HRV, the Power Spectral Density (PSD) from HRV between the intervals $[0, 0.2]$, $[0.2, 0.4]$, $[0.4, 0.6]$ and $[0.6, 0.8]$, and the maxima, minima, mean, median, standard deviation and range from the HRV histogram. The computed features were then concatenated into a single feature vector F_{ECG} to be used for the classification experiments.

IV. Results

After constructing the feature vectors for all the samples in the dataset, supervised classification experiments were conducted in order to examine the suitability of the proposed approach for the task of emotion recognition during human-horse interaction. Five classification algorithms were used in order to evaluate the performance of the examined features, namely Decision Trees (DT), Linear Discriminant Analysis (LDA), linear Support Vector Machines (SVM), SVM with the Radial Basis Function (RBF) kernel ($\gamma = 8.9$), and the k-Nearest Neighbour classifier for $k = 1$. In order to avoid over-fitting the trained models and to obtain a fair evaluation of the examined classifiers performance, a 10-fold cross validation process was followed. Classification performance for all the classifiers in terms of classification accuracy and the F1-score is provided in Table II, whereas the respective confusion matrices for each examined classification algorithm are shown in Fig. 3. It is evident that the SVM classifiers perform better than the 1-NN, the decision tree, and the LDA classifiers, both in terms of classification accuracy and the F1-score, with the SVM with the RBF kernel achieving the highest performance (74.21% accuracy and 72.18% F1-score).

V. Conclusion

In this work, the authors proposed an approach for a quantitative study of the complex emotional response that horses seem to elicit in humans, using physiological signals. To this end, the proposed quantitative approach consisted of the use of a portable system that is able to acquire various physiological signals (EEG, ECG, EMG) concurrently, while the users interact with the horses, and store them for further processing. The proposed system is a fully wireless and portable system that allows signal acquisition in remote environments while having a minimal effect on the subjects' ability to move. Furthermore, the use of a low cost computing device (Raspberry Pi) for gathering and storing the signals further reduces the requirements for power consumption, while having minimum weight.

The use of statistical features extracted from the ECG recordings of people interacting with horses was evaluated in this preliminary study for the task of identifying their emotional responses. Recordings were annotated as referring to positive or negative emotions by identifying relevant keywords from the video-recorded interviews of the participants. Supervised classification experiments showed that the proposed approach is suitable for identifying the emotional responses elicited by human-horse interaction, achieving a maximum classification accuracy of 74.21% and an F1-score of 72.18% when a Support Vector Machine classifier with the RBF kernel is used. The experimental results provide evidence about the suitability of the proposed approach for the task of affect detection for human-horse interaction.

Future work will include the use of the EEG and EMG recordings in combination with the ECG recordings in order to examine and evaluate the performance of a multi-modal approach for the task of affect recognition for human-horse interaction. Furthermore, the use of neural networks and deep learning techniques

1-NN

		Predicted	
		Positive	Negative
Actual	Positive	202	85
	Negative	90	127

(a)

Decision Tree

		Predicted	
		Positive	Negative
Actual	Positive	248	39
	Negative	104	113

(b)

Linear Discriminant Analysis

		Predicted	
		Positive	Negative
Actual	Positive	220	67
	Negative	101	116

(c)

SVM (Linear)

		Predicted	
		Positive	Negative
Actual	Positive	251	36
	Negative	97	120

(d)

SVM (RBF)

		Predicted	
		Positive	Negative
Actual	Positive	255	32
	Negative	98	119

(e)

Fig. 3: Confusion matrices for the examined classification algorithms: (a) 1-NN, (b) Decision Trees, (c) LDA, (d) SVM (Linear), and (e) SVM (RBF).

will also be examined in order to increase the classification performance of the proposed approach.

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